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Research on a New Hybrid Optimization Algorithm based on QPSO and FNN

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Abstract

Fuzzy neural network(FNN) is a neural network based on combining the advantages of the fuzzy theory and neural network. It has the characteristics of dealing with the non-linear and fuzziness and so on. Particle swarm optimization(PSO) algorithm is a population-based search algorithm by simulating the social behavior of birds within a flock. So the quantum PSO(QPSO) algorithm is proposed for optimizing the parameters of FNN in order to construct a new hybrid optimization(QPSO-FNN) algorithm in this paper. In the proposed QPSO-FNN algorithm, the quantum theory is used to improve the PSO algorithm, then the global optimization ability of QPSO algorithm is optimize the parameters of FNN model by putting these parameters in the particle encoding. The found optimal values are regarded as the parameters of FNN model to obtain the final QPSO-FNN method. Finally, the QPSO-FNN algorithm is used to solve the complex problem, the experimental results show that the QPSO-FNN algorithm takes on the shorter response time and higher solving accuracy.

Keywords: *Fuzzy theory; neural network; particle swarm optimization; quantum theory; hybrid optimization*

1. Introduction

Fuzzy neural network(FNN)[1] is a result based on combining fuzzy system with neural network. It has absorbed the advantages of fuzzy system and neural network, and it takes on the accurate fitting ability and learning ability of neural network and the strong structural knowledge expressing ability of fuzzy logic. The learning of fuzzy neural network has two parts: structure identification and parameter estimation. The structure identification is to determine the number of rules, the shape and number of the membership functions according to the certain performance requirements. The parameter estimation is to determine the further optimization of the parameters after the initial structure is determined. At present, the fuzzy neural network has a huge potential, there have obtained the fruitful research results in the recent years[2-5].

The FNN has good nonlinear mapping ability, self-learning adaptive ability and parallel information processing ability. But in the practical application, the FNN takes on some problems, such as the randomly given initial weights and thresholds, easy to fall into local minimum and unstable training result and so on. So a lot of experts and scholars proposed many methods for optimizing and improving the FNN model. Juang[6] proposed an evolutionary recurrent network which automates the

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design of recurrent neural/fuzzy networks using a new evolutionary learning algorithm. This new evolutionary learning algorithm is based on a hybrid of genetic algorithm (GA) and particle swarm optimization (PSO), and is thus called HGAPSO. Amitava *et al*.[7] proposed the possible development of particle swarm optimization (PSO)-based fuzzy-neural networks (FNNs) that can be employed as an important building block in real robot systems, controlled by voice-based commands. Amitava *et al*.[8] proposed the development of a neuro-fuzzy state-space model for flexible robotic arm on the basis of real sensor data acquired. The training problem of the neuro-fuzzy architecture has been configured as a highly multidimensional stochastic global optimization problem and improved variants of particle swarm optimization (PSO) techniques have been successfully implemented for it. Juang *et al*.[9] proposed a new approach for automating the structure and parameter learning of fuzzy systems by clustering-aided simplex particle swarm optimization, called CSPSO. Once a new rule is generated, the corresponding parameters are further tuned by the hybrid of the simplex method and particle swarm optimization (PSO). C.J. Lin and S.J. Hong [10] proposed a neuro-fuzzy network with novel hybrid learning algorithm. The novel hybrid learning algorithm is based on the fuzzy entropy clustering (FEC), the modified particle swarm optimization (MPSO), and the recursive singular value decomposition (RSVD). Zhang *et al*.[11] proposed a hybrid particle swarm optimization (HPSO) algorithm based on immune theory and nonlinear decreasing inertia weight (NDIW) strategy to tune manually parameters of fuzzy neural network controller for underwater vehicles. Liao *et al*.[12] proposed an integrated method of intelligent decoupling control as a solution to the problem of adjusting the zone temperatures in a regenerative pusher-type reheating furnace. The architecture of the controller is based on a fuzzy c-means clustering approach; and the weights are optimized by a hybrid particle swarm optimization (HPSO) algorithm, which integrates the global optimization of density-based selection and the precise search of clonal expansion in an immune system with the fast local search of particle swarm optimization. Lin *et al*.[13] proposed a recurrent functional link (FL)-based fuzzy neural network (FNN) controller to control the mover of a permanent-magnet linear synchronous motor (PMLSM) servo drive to track periodic reference trajectories. Youssef *et al*.[14] proposed the use of the adaptive particle swarm optimization (APSO) for adapting the weights of fuzzy neural networks (FNN) on line. The fuzzy neural network is used for identification of the dynamics of a DC motor with nonlinear load torque. Lin *et al*.[15] proposed an evolutionary neural fuzzy network, designed using the functional-link-based neural fuzzy network (FLNFN) and a new evolutionary learning algorithm. This new evolutionary learning algorithm is based on a hybrid of cooperative particle swarm optimization and cultural algorithm. Lin *et al*.[16] proposed a recurrent neural-fuzzy network (RNFN) based on improved particle swarm optimization (IPSO) for pattern recognition applications. The proposed IPSO method consists of the modified evolutionary direction operator (MEDO) and the traditional PSO. Catalão *et al*.[17] proposed a novel hybrid approach, combining wavelet transform, particle swarm optimization, and an adaptive-network-based fuzzy inference system for short-term wind power forecasting in Portugal. Oh *et al*.[18] proposed a polynomial-based radial basis function neural networks (P-RBF NNs) based on a fuzzy inference mechanism. The essential design parameters (including learning rate, momentum coefficient and fuzzification coefficient of the underlying clustering method) are optimized by means of the particle swarm optimization. Deng *et al*.[19] proposed a novel parallel hybrid intelligence optimization algorithm (PHIOA) based on combining the merits of particle swarm optimization with genetic algorithms for optimizing the structure and parameters of the fuzzy neural network. Isazadeh *et al*.[] proposed a new optimal adaptive dynamic load-shedding scheme for a large steelmaking industry with cogeneration units and an adaptive network-based fuzzy inference system (ANFIS) with a new training algorithm to increase the speed of the load-shedding scheme. Connolly *et al.*[21] proposed an incremental learning strategy based on dynamic particle swarm optimization (DPSO) to evolve heterogeneous ensembles of classifiers (where each classifier corresponds to a particle) in response to new reference samples. The DPSO is used to optimize fuzzy ARTMAP (FAM) neural networks for classification of facial regions. Tsekouras and Tsimikas[22] elaborated on the use of particle swarm optimization in training Gaussian type radial basis function neural networks under the umbrella of input-output fuzzy clustering. Yang *et al.*[23] proposed a novel self-constructing least-Wilcoxon generalized Radial Basis Function Neural-Fuzzy System (LW-GRBFNFS) and its applications to non-linear function approximation and chaos time sequence prediction. Zhao *et al.*[24] proposed a new STLF method(IPSO-F-BPNN.) based on combining improved particle swarm algorithm (IPSO), fuzzy theory (Fuzzy) and BP neural network (BPNN) to improve the STLF accuracy and speed. Ganesan *et al.*[25] proposed the model development and optimization of the DG power system using Particle Swarm Optimization (PSO). The goal was to minimize cost, maximize reliability and minimize emissions (multi-objective) subject to the requirements of the power balance and design constraints. Meng[26] proposed a new satisficing data envelopment analysis (DEA) model with credibility criterion, in which the inputs and outputs are assumed to be characterized by fuzzy variables with known membership functions. A hybrid particle swarm optimization (PSO) algorithm by integrating approximation method, neural network (NN) and PSO algorithm is proposed to solve the proposed DEA model. Kuo *et al.*[27] proposed a particle swarm optimization (PSO)-based fuzzy neural network (IOAP-FNN) to determine the relationship between the RFID signals and the position of a picking cart for an RFID-based positioning system. Liu *et al.* [28] proposed a particle swarm optimization based simultaneous learning framework for clustering and classification (PSOSLCC). PSOSLCC has been extensively compared with fuzzy relational classifier (FRC), vector quantization and learning vector quantization (VQ+LVQ3), and radial basis function neural network (RBFNN). Das *et al.* [29] applied Artificial Neural Network (ANN) trained with Particle Swarm Optimization (PSO) for the problem of channel equalization. Ling *et al.* [30] proposed an intelligent swarm based-wavelet neural network for affective mobile. The contribution is to develop a new intelligent particle swarm optimization (iPSO), where a fuzzy logic system developed based on human knowledge is proposed to determine the inertia weight for the swarm movement of the PSO and the control parameter of a newly introduced cross-mutated operation. Peng and Chen[31] proposed a symbiotic particle swarm optimization (SPSO) algorithm for compensatory neural fuzzy networks (CNFN). The CNFN model using compensatory fuzzy operators makes fuzzy logic systems more adaptive and effective. Wang *et al.*[32] proposed a multiple BP neural networks soft sensing modeling of grinding granularity based on fuzzy c-means (FCM) clustering algorithm.

In this paper, in order to further improve the performance of the FNN, the quantum theory is used to improve the PSO algorithm, then the global optimization ability of QPSO algorithm is optimize the parameters of FNN model by putting these parameters in the particle encoding. The found optimal values are regarded as the parameters of FNN model to obtain the final QPSO-FNN method. The effectiveness of the QPSO-FNN method are verified on the Matlab platform.

The rest of this paper is organized as follows. Section 2 briefly introduces the particle swarm optimization (PSO) algorithm and quantum particle swarm optimization(QPSO) algorithm. Section 3 briefly introduces fuzzy neural network(FNN). Section 4 proposed a new hybrid optimization(QPSO-FNN) algorithm. Section 5 gives the digital simulation and performance analysis. Finally, the conclusions are discussed in Section 6.

2. The PSO and Quantum PSO (QPSO)

2.1. The PSO Agorithm

Particle swarm optimization(PSO) algorithm is a population-based search algorithm. The positions of particles within the search space are changed based on the social-psychological tendency of individuals in order to delete the success of other individuals. The variety of one particle is influenced by the experience, or knowledge in the swarm. The consequence of modeling is that the search is processed in order to return to previously successful regions in the search space. Namely, the velocity(V) and position(X) of each particle will be changed by the particle best value ($Pbest$) and global best value ($Gbest$). The velocity updating and position updating of each particle are shown:

$$V_{ij}(t+1) = \omega V_{ij}(t) + c_1 r_1 \left(Pbest_{ij}(t) - X_{ij}(t)\right) + c_2 r_2 \left(Gbest_{ij}(t) - X_{ij}(t)\right) \tag{1}$$

$$X_{ij}(t+1) = X_{ij}(t) + V_{ij}(t+1) \tag{2}$$

where $V_{ij}(t+1)$ is the velocity of the particle i at the j iteration, $X_{ij}(t+1)$ is the position of the particle i^{th} at the j^{th} iterations. ω is the inertia weight to control the impact of previous history of the velocity. t denotes the iteration number, c_1 is cognition learning factor, c_2 is social learning factor, r_1 and r_2 are random numbers on [0, 1], which denote remembrance ability.

The flow of the standard PSO algorithm is shown in Figure 1.

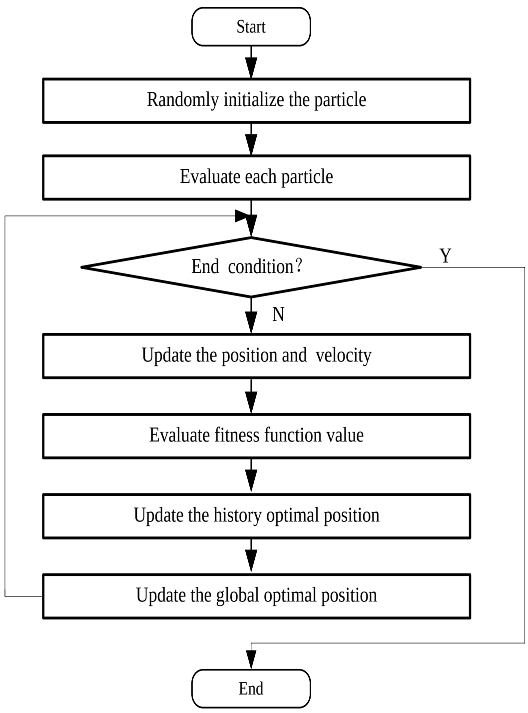

Figure 1. The Flow of the Standard PSO Algorithm

2.2. The QPSO Agorithm

In the standard PSO algorithm, the particle realizes the search within the limited search space by using the determined certain line. The velocity and position of each particle will restricted by various rail. The PSO algorithm can not guarantee that the probability is 1 for the global optimal solution. But in the quantum world, the movement paths of the particles are not be restricted. The evolution process complies with the equation of Schrodinger, so the velocity and position of each particle can not be determined simultaneously. In the PSO system, if the single particle has the quantum behavior, the PSO algorithm will perform the operation according to the given rules. In the PSO algorithm, the quantum state of one particle is described by the wave function $\psi(x,t)$. When the wave function $\psi(x,t)$ is determined, the average measured of each particle is completely determined. So a quantum particle swarm optimization (QPSO) algorithm is proposed by Sun, the performance of the QPSO algorithm is far superior to the standard PSO algorithm.

The QPSO algorithm defines the particle in the determined one quantum space of the probability density function. The state of each particle is no longer expressed by the velocity and position. The quantum state is converted into normal state the conversion of Carlo Monte method. The updating equation is described:

$$\begin{cases} x_i(t+1) = p_t \pm \alpha * | Mbest_i - x_i(t) | * \ln \dfrac{1}{\mu} \\ p_t = \dfrac{a * Pbest_t + b * Gbest_t}{a+b} \\ \alpha = \dfrac{(\alpha_1 - \alpha_2) * (T_{\max} - t)}{T_{\max} + \alpha_2} \\ Mbest_t = \dfrac{\sum_{i=1}^{M} Pbest_t(i)}{M} \end{cases} \tag{3}$$

where α is variable contraction factor of t, the value of α is changed with the value of t. The α is used to control the speed of convergence. α_1 and α_2 are the starting value and the end value of variable contraction factor α. $T_{\max}$ is the maximum number of iteration. $Mbest_t$ is the average of the local search optimal position of each particle in the population. p_t is random position vector between $Pbest_t$ and $Gbest_t$, M is the number of particles in the population. $Pbest_t$ is position vector of the searched optimal solution of the r^{th} particle. t is the number of the current iteration, a, b, μ are random number $[0,1]$.

3. The FNN Model

Fuzzy theory and neural network model are found without the mathematics model of dynamic characteristic Fuzzy theory is to describe the regular expert knowledge, experience or operation data, and the neural network is used to train sample data. Fuzzy neural network is to combine the fuzzy theory and neural network. The FNN combines the advantages of fuzzy theory and neural network. It takes on great advantages for dealing with the non-linear and fuzziness and so on. In intelligent information processing, the FNN has a huge potential, more and more experts and scholars contribute to this area and the fruitful research results are obtained in the recent years. The FNN model is composed of five layers. The function of each layer is illuminated:

(1) Input layer In this layer, input vectors may be accurate numerical vector or fuzzy value. The followed expression is:

$$O_i^1 = I_i = x_i, i = 1,2,3,\cdots,n \tag{4}$$

(2) Fuzzification layer In this layer, the function is to fuzzify the input variable. The membership function adopts Gaussian function because of providing with the good smoothness of the Gaussian function. The followed expression is:

$$\mu_{ij} = \exp[-\frac{(x_i - c_{ij})^2}{\sigma_{ij}^2}],\ i = 1,2,\cdots,r;\ j = 1,2,\cdots,u \tag{5}$$

where in the j[th] neuron, the μ_{ij} is the i[th] Gaussian function, the σ_{ij} is the i[th] Gaussian function standard deviation, the c_{ij} is the i[th] Gaussian function center, r is the number of input dimension, u is the number of neuron. The output result of the j[th] neuron is shown:

$$O_j^2 = \exp[\sum_{i=1}^{r} \frac{(x_i - c_{ij})^2}{\sigma_{ij}^2}],\ j = 1,2,\cdots,u \tag{6}$$

(3) Fuzzy reasoning layer or fuzzy membership layer In this layer, one neuron denotes on fuzzy rule. The followed expression is:

$$O_j^3 = w_{a1}O_1^2 \times w_{a2}O_2^2 \times \cdots \times w_{au}O_u^2 = \prod_{j=1}^{u} w_{aj}O_j^2 \tag{7}$$

(4) Anti-fuzzification layer In this layer, the clear output of the fuzzy neural network is realized and the anti-fuzzification algorithm is provided with the global approximability. We adopt the general fuzzy method of the gravity solution in this paper. The expression is:

$$O_j^4 = \frac{O_j^3}{\sum_{j=1}^{u} O_j^3},\ j = 1,2,\cdots,u \tag{8}$$

(5) Output layer The precision calculation is realized by the followed expression:

$$y = \sum_{j=1}^{u} w_{bj}O_j^4,\quad j = 1,2,\cdots,u \tag{9}$$

where, w_{bj} is the connection weight of the FNN model.

4. A New Hybrid Optimization (QPSO-FNN) Algorithm

The FNN is to use the sum of squared error as the objective function and the gradient method for solving the minimum value on the essence. The QPSO algorithm is to belong to the global optimization process on the essence. In addition, in the process of solving many optimization problems, it is difficult to rely on numerical equation derivation for selecting the optimization direction, thus the classical fuzzy neural network algorithm is obviously weak. The QPSO algorithm is the most widely used in the field of optimization. Therefore, it can be considered in the fuzzy neural network training, the QPSO algorithm is used to optimize the parameters of the input nodes, hidden layer nodes, input weights, output weights, and threshold of fuzzy neural network. Then the combination of the obtained network parameters is further accurately optimized in order to establish a stable, global, fast fuzzy neural network model, which also has a strong memory ability and generalization ability.

The QPSO algorithm is used to repeatedly optimize the initial weights vector and threshold parameters combination, including the input weight, output weight, input node threshold and output node threshold. The elements of position vector x in the particle swarm are the connection weights and thresholds between all nodes of the fuzzy neural network. They will be optimizing until the fitness of the solution is no longer meaningful increasing, that is the quality of the solution population tends to be stable. At this time, the obtained combination of parameters is close to the best required combination. On this basis, after decoding, the fuzzy neural network is used to further accurately optimize the network parameters until the optimal network parameters are searched. Then the best accurately combination of parameters is obtained. Because the QPSO algorithm is used to replace the initial optimization of fuzzy neural network, the parameter optimization based on the near optimal solution is executed in order to effectively improve the searching speed and precision of the fuzzy neural network. The size of QPSO algorithm is N, each particle is a D dimensional vector. The position vector x of particle represents the input weight, output weight, input node threshold and output node threshold. The initial population is randomly generated. the position of particle is changed according to the speed of particle. The mean square error of fuzzy neural network is described:

$$F = \frac{1}{n}\sum_{i=1}^{n}\sum_{k=1}^{m}(d_i - d_k)^2 \tag{10}$$

where d_i is the actual output of fuzzy neural network, d_k is the target output of fuzzy neural network, n is the number of training samples, m is the number of output nodes. This function a nonlinear function with multiple minima. The training process of fuzzy neural network is to adjust the input weight, output weight, input node threshold and output node threshold of fuzzy neural network, until the error of the function reaches the minimum value.

The steps of the new hybrid optimization(QPSO-FNN) algorithm are described as follows:

Step1: initialize

Determine the topological structure of the fuzzy neural network according to the input and output samples of fuzzy neural network. Randomly initialize the population size(N),the position(x_i) and velocity(v_i), $x_i \in [x_{\min}, x_{\max}]$, $v_i \in [v_{\min}, v_{\max}]$ .Initialize the cognition learning factor(c_1), social learning factor(c_2), the initial inertia weight(ω), error accuracy of fitness(ε), the number of maximum iteration($T_{\max}$).

Step2: Calculate the fitness value

Calculate the fitness value of each particle according to the mean square error function of fuzzy neural network. The position of the initial particle is recorded the local optimal value($Pbest$), the found particle with the best fitness value in the population is regarded the global optimal value($Gbest$).The extreme value of the particle is the optimal weight of fuzzy neural network in the next iteration.

Step3: Analyze and compare

The QPSO algorithm is used to search the optimal value of parameters for fuzzy neural network. For each particle, If the current fitness value is better than the local optimal value ($Pbest$), then the local optimal value ($Pbest$) is replaced by the current fitness value. And the local optimal value($Pbest$) is analyzed and compared with the global optimal value($Gbest$). If the local optimal value ($Pbest$) is better than the global optimal value($Gbest$),the global optimal value($Gbest$) is replaced by the local optimal value ($Pbest$).

Step4: Update the position and velocity

The current position and search velocity of particle are adjusted according to the equation (1) and (2).

Step5: If the number of iteration reaches the maximum number of iteration, or the error accuracy of current fitness value is less than the error accuracy (ε),the QPSO-FNN algorithm is terminated. Output the optimal result. Otherwise, go to Step 3.

Step 6. Optimize the parameters of the fuzzy neural network

The key of the parameters of the fuzzy neural network is to find the learning parameters of the FNN. A unit step function δ is introduced into this paper.

Step 7. Train the fuzzy neural network

Input the training samples to train the corresponding fuzzy neural network. The optimization process of connection weights of the fuzzy neural network is an iterative process. In the optimization process of connection weights of the fuzzy neural network, the given sample set is classified in order to guarantee that the training adopts the training set, which is not the same.

Step 8. Obtain the best fuzzy neural network(QPSO-FNN) model.

5. Digital Simulation and Performance Analysis

In order to the performance of the best fuzzy neural network(QPSO-FNN) model based on QPSO algorithm and FNN, the digital simulation experiment is executed. FNN is a 3 layer structure of the forward network, the activation function of hidden layer node is described:

$$O_i = \exp[-(w_{ij} x_j + w_i)^2] \tag{11}$$

Because the initial values of parameters could seriously affect the experiment result, the most reasonable initial values of these parameters are obtained by testing and modifying. So the initial parameters of the QPSO algorithm are determined by some preliminary experiments in order to obtain the best performance for the QPSO algorithm. The parameters of the QPSO algorithm are set: population size m = 50, iteration times $T_{\max}$ =1000, max velocity $v_{\max}$ =80, learning factor $c_1 = c_2$ =2.0, initial inertia weight w_0 =0.9, r_1 and $r_2 \in [0,1]$. The number of neurons in hidden layer is determined by the QPSO algorithm. The environments are followed: the Pentium CPU 2.40GHz, 2.0GB RAM with the Windows operating system, Matlab2012b. The experimental simulation results are shown in Figure 2~Figure 5.

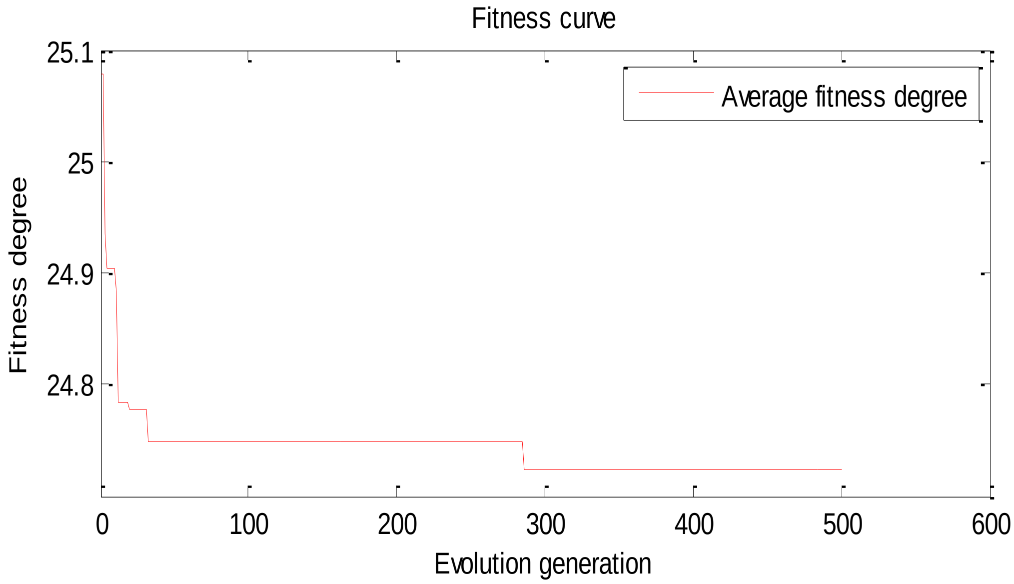

Figure 2. Average Fitness Curve

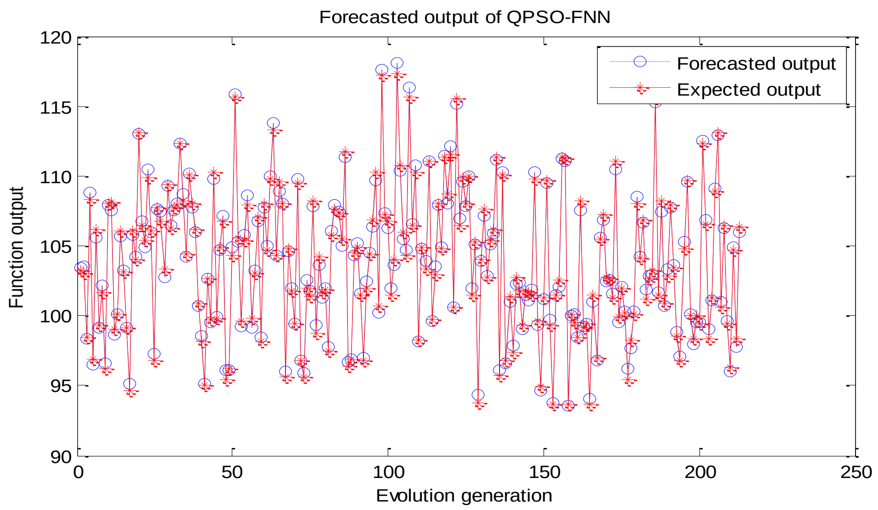

Figure 3. Comparison of QPSO-FNN between the Forecasted and Expected Outputs

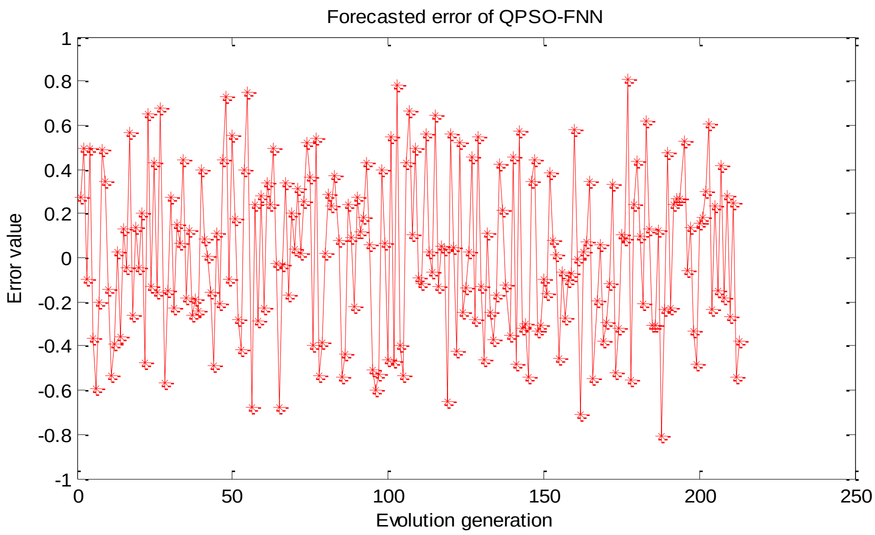

Figure 4.The Forecasted Error of QPSO-FNN

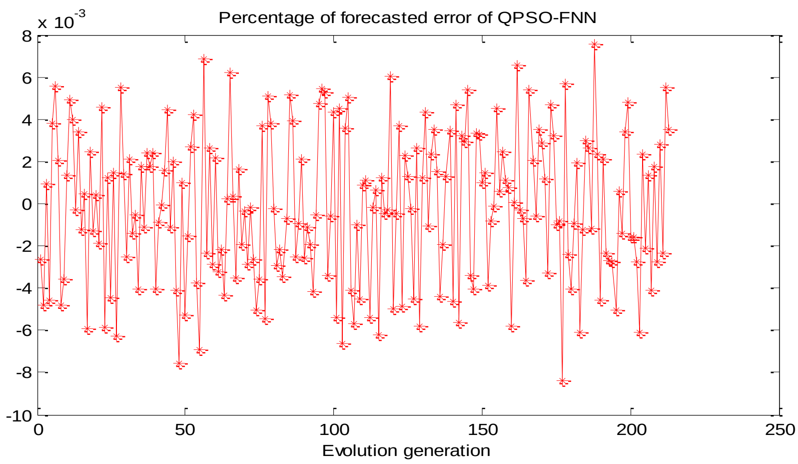

Figure 5.The Percentage of Forecasted Error of QPSO-FNN

As can be seen from the Figure 2, when the time of the iteration is 292, the fitness value is becoming to be stable, the stable fitness value is 24.73. As can be seen from Figure 3, the forecasted output value is very close to the expected output value by using QPSO-FNN. At the same time, the forecasted output value is equal to the expected output value for some iterations. As can be seen from Figure 4 and Figure 5, the forecasted error is small, the percentage of forecasted error of QPSO-FNN is extremely small. The percentage of forecasted error of QPSO-FNN is extremely small. The experimental results for the QPSO-FNN algorithm show that the QPSO-FNN algorithm takes on the shorter response time and higher solving accuracy.

6. Conclusion

In order to overcome the weak generalization ability for the FNN by using BP neural network, the QPSO algorithm is used to optimize the FNN in order to propose a QPSO-FNN model. There show the strong performances for optimizing the FNN based on the QPSO algorithm. The QPSO-FNN algorithm is a simple algorithm, and can greatly improve the learning speed, accuracy and robustness. This algorithm makes full use of the global search characteristics of QPSO algorithm to effectively avoid to fall into local minimum for BP neural network. And it does not require derivative information, so as to avoid the complexity of the back error propagation of BP algorithm. At the same time, because the QPSO-FNN algorithm does not require derivative information, the optimization performance index can be extended to the complex condition in order to provide a more extensive space for selecting the activation function and the performance function of the fuzzy neural network.

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